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IN-DEPTH REVIEW ON MACHINE LEARNING MODELS FOR LONG-TERM FLOOD FORECASTING

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ABSTRACT

Flood is a natural disaster that can cause damage in human life, infrastructure, and socioeconomics. Forecasting the flood is essential to provide sustainable flood risk management for the people. Long-term flood forecasting is very important to provide early knowledge and information for decision maker in minimizing the impact of flood. Early warning can also be disseminated to the potential flood victim and area while proper action can be triggered such as mitigation and evacuation process. The development of long-term flood forecasting model has growing recently with the adoption of machine learning models. It has spark interest among researchers to explore the ability of machine learning characteristics in providing accurate forecasting. Nevertheless, the machine learning models has shown uncertainty and instability in their forecast. The goal of this paper is to provide an understanding and in-depth review of machine learning models in long-term flood forecasting. It includes investigating machine learning models used for long-term flood forecasting and performing comparative assessment in the type of parameters, pre-processing methods and performance measurements used by the models. This review indicates that machine learning models has widely been used involving single and hybrid models for long-term flood forecasting. Various parameters or flood variables have been used as the predictors. The performance of the forecast has been found to be improved through the hybridization of the model. Evaluation of the machine learning models can be done through various performance measurement that prove the models can provide acceptable forecast. The outcome of this study will help future researchers by providing insights of the current progress in the use of machine learning in long-term flood forecasting.

Keywords: *Flood Forecasting, Machine Learning Models, Hybrid Model, Literature Review, Hydrological Forecasting*

1. INTRODUCTION

Flood is a common natural disaster that occurred around the world which giving a huge impact to lives, economic and social. It can bring a great destruction to the people and infrastructure. The advancement of technology has enabled flood forecasting to be done to alleviate damages caused by flood. Flood can be forecasted within several define lead time. Based on [1], the lead time of the forecast can be categorized by short-term which up to 2 days, medium-term up to ten (10) days, long-term for more than ten (10) days and seasonal if it takes several months.

The need for such forecast especially in long-term period is an important significance to provide robust disaster management strategies, including adaptive and mitigation measures. An optimized forecast not only help in facilitating stakeholder's decision but also to the socio-economic sectors. Flood forecasting with different lead time is fundamentally challenging and complex as the climate condition of the nature is very dynamic. Many forecasting models been developed nowadays are data-specific involving simplified assumptions.

One type of the model that been widely used in flood forecasting is known as physical based model. Physical based model is a description method of the hydrological process for targeted basin [2]. One of the predictors that can be used to forecast flood is watershed. There are fourteen (14) physical models has been reviewed by [3] that can be used to forecast watershed using storm water event. The physical models including Agricultural NonPoint Source pollution model (AGNPS), Areal Nonpoint Source Watershed Environment Response Simulation (ANSWER), DR3M/DR3M QUAL, Dynamic

Watershed Simulation Model (DWSM), Gridded Surface/Subsurface Hydrologic Analysis (GSSHA), Hydrologic Engineering Center–Hydrologic Modelling (HEC-HMS), Hydrological Simulation Program—Fortran (HSPF), Kinematic Runoff and Erosion model (KINEROS), MIKE Syst`eme Hydrologique Europ´een (MIKESHE), MIKE URBAN, Precipitation-Runoff Modelling System (PRMS), Sedimentology by Distributed Modelling, Techniques—version III (SEDIMOT III), Storm Water Management Model (SWMM) and Technical Release 55 (TR-55).

Although physical based model is expected to be more accurate than the approximations model, it is inefficient due to its complexity in numerical schemes. Physical model that utilize the 2D shallow-water equation has long been used to forecast runoff [4][5][6], flows [7][8], and flood hazard map [9]. These predictors are often used to forecast flood. The development of physical model as such needs a great amount of data, complex calculation and comprehensive knowledge and expertise of the hydrological data and process underneath [10]. Although physical based model can provide an acceptable forecast, but there is also event in which it failed to properly predict, resulting massive disaster [11]. In recent development of physical based model, hybridization has been adopt to elevate the performance of such models [12].

The use of extensive amount of data in physical based model has led to more processing time that can increase processing cost. Furthermore, it needs a very depth knowledge of the related process involved to provide forecast. To overcome this drawback, data driven models has been widely adopted among researchers. Data driven models is based on stochastic, empirical and theory concepts which is flexible and using minimum data requirement [13].

To improve flood forecasting it is a trending practices among the researcher to grasp different type of data such as climate indices into the forecast model [14]. Among the data driven models developed for flood forecasting are Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA). ARMA and ARIMA are based on Flood Frequency Analysis (FFA) where they interprets past record of hydrological events for the probability of future occurrences [15]. ARMA and ARIMA has been used either one or both to forecast monthly inflow [16], water demand [17], inflow dam reservoir [18] and flood events [19] using various type of flood variables such as water discharge, water level, temperature and rainfall. Extensions of these models such as Seasonal Autoregressive Integrated Moving Average (SARIMA) [20] and Multiplicative Seasonal Autoregressive Integrated Moving Average (MSARIMA) [19] are used in flood forecasting by supporting seasonal component.

Advance type of FFA called Regional Flood Frequency Analysis (RFFA) estimate the magnitude of flood events for various return period in homogeneous region [21]. RFFA has been reported to be more efficient than the physical model with less predictor variables [22]. Multiple Linear Regression (MLP) is another data-driven model used in flood forecasting [23]. Although MLR can exhibit acceptable forecast, but it provides lower performance and only reliable when strong linearity is shown between variables [24].

Physical based model and data-driven model has been a great tool in forecasting the hydrological events, but they imposed their own limitation such as complex calculation and more processing time in physical based model and instability in model performance for data-driven models. Due to these limitation, researchers now has increasingly using progressing advanced data driven model such as machine learning [25]. In machine learning, forecasting is made using historical data without requiring knowledge about the underlying physical processes [14]. Comparing with fully distributed model, machine learning has achieved high predictive potential with less complex, less development time and minimal inputs [26][27]. The use of machine learning has demonstrated its ability to perform acceptable forecast outperforming conventional physical model and can accommodate the non-linearity of the hydrological events. [27].

Machine learning models such as Artificial Neural Networks (ANN) [28][29][30], Random Forest [31], Extreme Learning Machine (ELM) [32], Support Vector Machine [33], Support Vector Regression (SVR) [34][35], and Neuro Fuzzy [14] has been reported to be effective in forecasting short-term and long-term flood with higher accuracy. Although individual machine learning algorithm has showing significant result in flood forecasting, but the performance of such models can be improved through hybridization with other machine learning methods. Through hybridization it not only provides faster learning process and stronger generalization ability [32][36], but also increase the forecasting accuracy [36][37][38].

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The ability of machine learning model to learn from the historical data can be a shortcoming if the data is scarce, thus impacting the performance of such model. Therefore, optimization in data pre-processing is essential to overcome this problem. The use of pre-processing method to optimize the input selection such as Wavelet Transform [39][40], Ensemble Empirical Mode Decomposition (EEMD) [41], Genetic Algorithm (GA) [22] and correlation analysis [27] has been reported to improve the performance and accuracy of the forecasting.

As machine learning has increasingly growing and widely adopted to provide flood forecast by researcher, it provides uncertainty and instability in the forecast. It is important to have an in-depth knowledge on how this model can be used and tuned in providing acceptable and accurate performance. This paper tends to provide insights regarding various machine learning algorithms for long-term flood forecasting. The contributions of this survey are to investigate machine learning models used for long-term flood forecasting and performing comparative assessment in the type of parameters, pre-processing methods and performance measurements used by the models. Analysing the type of parameters and pre-processing methods is crucial as it can affect how the model behave, while performance measurement will guide the researcher to select the right measurement to evaluate the model.

2. RESEARCH METHODS

Systematic Literature Review (SLR) was conducted to identifies and provide deep understanding regarding the machine learning method in long term flood forecasting. This review is based on guidelines by Kitchenham and Brereton [42] in which it allows us to discover and synthesize information in published materials systematically. It was based on pre-defined question of the research to provide concise analysis and valuable information to the research community.

This SLR is performed by following a formal process with define steps which make it more objective and repeatable. This process is fundamental towards the acceptance and appreciation of the conclusion of this study. SLR stages divided into 3 main phase which are Planning the Review, Conducting the Review, and Reporting the Review. Table 1 summarize the activities done for each stage in every phase of this study.

Table 1: SLR stages

Phase 1: Planning the Review	Formulating Research Questions
	Developing Review Protocol
	Identifies Inclusion and Exclusion Criteria
Phase 2: Conducting the Review	Defining Search Strategy and Selection Process
	Primary Study Selection
	Quality Assessment
Phase 3: Reporting the Review	Data Extraction and Synthetization

Conducting a formal and organized search process is crucial in this review. It helps in finding all relevant and related literature though available online digital resources that matched with the search criteria. In this study, search for literatures has been conducted through six online repositories including automatic search that involves IEEE Explorer, ACM Digital Library, Science Direct, Scopus and Springer. Other than that, Google Scholar is used in the manual search process. These repositories were selected based on its relevance to the topic.

The automatic search was conducted using keyword search query consists of two main search terms. The lead time of the forecast is considered as Term 1 (<L_1-L_n>) and term most often used to describe flood prediction as Term 2 (<P_1-P_n>). Term 1 included "long term" OR "monthly" OR "seasonal" OR "yearly" OR "annually" and Term 2 included "flood forecasting" OR "flood prediction" OR "flood estimation" OR "flood analysis". Figure 1 described the flowchart of the search queries. Search results with only preview content are not included. A total initial search of 984 papers is found by this keyword search query.

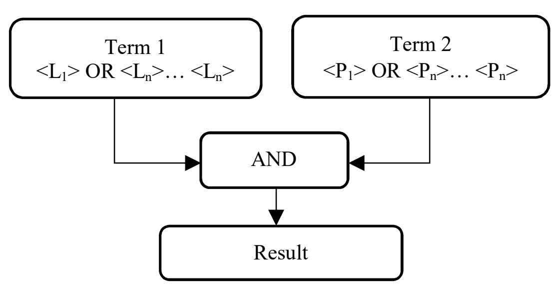

Figure 1: Automatic search query method

From the initial search result of 984 papers, the total of primary papers include in this study is 40 papers after automatic and manual searching. Quality assessment is conducted for all the primary papers to assess their quality.

The following section will present the analysis results and discussion in which Section 3 will present the machine learning models developed for long-term flood forecasting, Section 4 presents the comparative assessment of the machine learning model for long-term flood forecasting including flood variables, pre-processing techniques and performance measurement used. Section 5 presents the conclusion of this study.

3. MACHINE LEARNING MODELS IN LONG-TERM FLOOD FORECASTING

Long-term flood prediction is very important to support water resources management and reducing the impacts of flood. It helps in evacuation process and giving knowledge to the citizens regarding potential floods. Long-term forecasting for over 10 days, monthly, annually, or seasonally is done to assess the potential of flood in specific location and region. The use of machine learning model has sparked an interest among researcher towards the exploration and research in the field of long-term flood forecasting. Machine learning model has widely been used to forecast hydrological events such as annual and monthly inflow [43], monthly and annual runoff [44]–[46], monthly discharge [47][48], flood quantiles [22], monthly flow rate [49], monthly ground water level [50][51], monthly and seasonal rainfall [52]–[57], monthly streamflow [33], [40], [65]–[67], [41], [58]–[64], monthly and seasonal precipitation [68], and monthly and annual water level [69][70].

The flow of the development of machine learning model can be summarized as in Figure 2. This flow depicts general flow and variations can be found among researchers in which involves the use of the original datasets without pre-processing and including validation process in between training and testing. In developing machine learning model for long-term flood forecasting, data are gathered from reliable resources. Then data are pre-processed in which original datasets is transformed to a new format and be prepared as an input to the model. Pre-processing is crucial as it determine the input selection for the model. Model development stage involved using tools or programming language to transform algorithm into working model. This model then will be evaluated during training and testing of the model.

The development of machine learning model for long-term flood forecasting can be classified as single or hybrid model. Single model applies only one of machine learning methods to produce the forecast, while hybrid model using different machine learning method in a form of integration or ensemble.

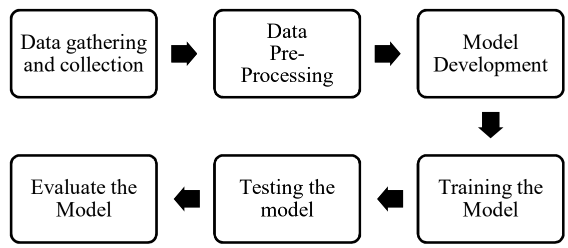

Figure 2: Flow of Machine Learning development for long term flood forecasting

Integration involved integrating one machine learning model with another machine learning model, data-driven model, physical based model, or other conventional methods. While ensemble can be done by combining multiple models through aggregating, bagging, boosting, blending, or stacking techniques. The taxonomy of the machine learning methods in this study is depicts in Figure 3.

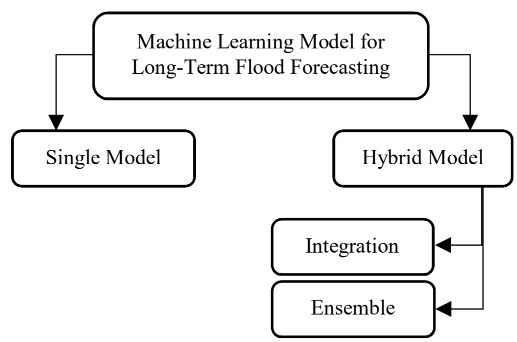

Figure 3: Taxonomy of machine learning models in long-term flood forecasting

3.1 Machine Learning in Long-Term Flood Forecasting Using Single Model

In the development of long-term flood forecasting using single model, it is revealed that Artificial Neural Networks (ANN) is the most single machine learning models that been used to forecast long-term flood. Other methods include Support Vector regression (SVR), Support Vector Machine (SVM), Decision Tree (DT), TreeBoost (TB), Random Forest (RF), Extreme Learning Machine (ELM), General Regression Neural Network

(GRNN), Multilayer Perceptron (MLP), Radial Basis Function Neural Networks (RBFNN), Recurrent Neural Network (RNN) and Autoregressive Neural Network (ARNN).

ANN has been widely developed to forecast monthly rainfall in [71][52][53][56][57] which then been compared with existing model used in particular location. The existing model are named Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [71], General Circulation Model (GCM) [52], and Predictive Ocean Atmosphere Model for Australia (POAMA) [53][56][57]. Rainfall data and climate indices has been used as their predictors. These studies indicates that ANN provide a better rainfall forecast prediction than GCM and have better skill forecasting than POAMA. ANN has the advantages in quantifying the expected rainfall amount and not just the categorization of above or below median [56]. In the other hand the TOPSIS is reported to outperform ANN although the performance during training phase is better but do not show acceptable result during validation phase. In this case, large number of predictors is needed to gain high performance for the ANN model comparing to TOPSIS. This indicate that although ANN is a promising tool to forecast the rainfall, but it can produce uncertain results depending on the type and amount of data used for particular geographical location.

ANN has also been developed along with SVR in streamflow forecasting. ANN prove to have superiority over SVR in predictability performance [72]. Although both ANN and SVR can deal with the non-linearity of the time series data, SVR can minimize the structural risk, thus avoiding model over-fitting [72]. SVR also has been reported to outperform ANN in monthly streamflow forecasting with low forecasting error [47]. In the other hand, ANN models that used multilayer perceptron (MLP) and radial basis function (RBF) has proven to be more reliable than the support vector machine (SVM) in forecasting river flow with the incorporation of the time index within the inputs [73]. MLP also has improve the accuracy of precipitation simulation in arid climates by importing exogenous variables to the networks and using bigger time scales [68]. MLP has also proven to outperformed Adaptive-Network-Based Fuzzy Inference System (ANFIS) in the forecasting of seasonal precipitation based on different large-scale climate signals [74].

Another type of neural networks that recently gain interest among researchers is Extreme Learning Machine (ELM). ELM is a model that use single-layer feedforward neural networks that randomly determined the hidden neurons and learns the pattern embedded in the input variables [67]. ELM has proven to forecast long-term streamflow with better accuracy over another model such as ANN [67] [70],SVR and GRNN [75]. In monthly ground water level forecasting, ELM has proven it superiority over ANN and RBF in [50] and SVM in [51]. ELM has been found to simplifies the entire training process and reduce the computational time of the training neural networks [76]. Table 2 summarized the single models of machine learning for long-term flood forecasting.

While ANN and ELM are based on connected neurons where such happened in human brains, another model which called Tree model is one of machine learning model that use the representation of tree in which it can identify way of splitting data set based on certain conditions. Ref [60] compared three tree models for monthly streamflow forecasting using streamflow data. It has been found that Random Forest has provide better performance than TreeBoost and Decision Tree techniques. This is due to random forest consist of parallel decision trees that grown together until the optimal results are met. Other tree model such as M5-Tree has been reported to be underperformed comparing to Least Square Support Vector Regression (LSSVR) when modelling monthly streamflow with the influenced of periodicity component as an external sub-set [58].

3.2 Machine Learning in Long-Term Flood Forecasting Using Hybrid Model

Machine learning models for long-term flood forecasting also can be found in the term of hybrid model. Hybrid models are developed by integrating, ensemble or combining multiple machine learning methods to produce forecast with acceptable performance and accuracy. Some of the researcher tend to integrate machine learning with other conventional methods such as physical method in the effort to find enhanced model performances.

In flow forecasting, various hybrid models are developed by integrating optimizing methods for the inputs with the machine learning models. Optimization methods such as Discrete Wavelet Transform (DWT), Empirical Mode Decomposition (EMD), Ensemble Empirical Mode Decomposition (EEMD) and Genetic Algorithm (GA) are among that capture the attention of the researchers. The use of hybrid model such as DWT-ANN[40], DWT-

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RBFNN[44], DWT-SVR [33] has been proved to provide a precision forecasting for monthly streamflow. In these models the use of multiple type data which is rainfall and discharge has provided greater forecasting accuracy than only using the discharge data. The use of rainfall data has given a significant impact to the forecasting performance. Wavelet-Extreme Learning Machine (WA-ELM) has been developed for forecasting monthly flow in semi-arid region in Iraq and been compared with single ELM [39]. The results indicate that the best performance of these two models is influenced by the different period of antecedent data as predictors.

In the other hand, the use of hybrid models using Wavelet based has indicates that Wavelet-ELM (W-ELM) is more suitable than Wavelet-Neural Network (W-NN) model for long-term runoff forecasting [64]. Unlike W-ELM, W-NN model has failed to address the non-linear characteristics of the rainfall-runoff process.

Empirical Mode Decomposition based model also been used in the long-term runoff forecasting.

Table 2: Machine learning for long-term flood forecasting using single model

Reference	Method Proposed	Forecasting Type	Lead Time	Flood Variables	Comparison Method	Country
[69]	ANN	Water Level	Annually	Rainfall, Water Level	LR, ARIMA	Malaysia
[71]	ANN	Rainfall	Monthly	Rainfall, Climate signals	TOPSIS	Canada
[52]	ANN	Rainfall	Monthly	Rainfall, Climate Indices, Temperature	GCM	Australia
[58]	LSSVR, MARS, M5-Tree	Stream Flow	Monthly	Streamflow	MLR	Iraq
[53]	ANN	Rainfall	Monthly	Rainfall, Atmospheric, Temperature, Composite, Climate Indices	POAMA	Australia
[47]	SVR	Discharge	Monthly	Discharge	ANN-ELM, GPR	India
[48]	ARNN	Discharge	Monthly	Discharge, Water Level	ARMA, ARIMA	India
[77]	ANN	Precipitation	Monthly	Rainfall, Climate Signals	ANN with different signal	Iran
[60]	DT, TB, RF	Stream Flow	Monthly	Stream Flow	Compare each of the proposed method	Iraq
[73]	ANN, SVM	River Flow	Monthly	River Flow	Compare each of the proposed method	Iran
[72]	SVR, ANN	Discharge	Monthly	Discharge	Compare each of the proposed method	India
[68]	ANN	Precipitation	Monthly	Precipitation, Climatic Data	NAR, NARX	Iran
[50]	ELM	Ground Water Level	Monthly	Precipitation, Evaporation, Ground Water Level	ANN, RBFNN, ARMA	Iran
[51]	ELM, SVM	Ground Water Level	Monthly	Rainfall, Temperature, Evapotranspiration, Ground Water Level	Compare each of the proposed method	Canada

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Reference	Method Proposed	Forecasting Type	Lead Time	Flood Variables	Comparison Method	Country
[61]	ELM	Stream Flow	Monthly	Stream Flow	ANN	Malaysia
[75]	ELM	Stream Flow	Monthly	Stream Flow	SVR GRNN	Iraq
[74]	MLR, MLP	Precipitation	Seasonal	Precipitation, Climate signal	ANFIS	Iran
[56]	ANN	Rainfall	Monthly	Rainfall, Atmospheric, Temperature, Composite, Climate Indices	POAMA	Australia
[57]	ANN	Rainfall	Monthly	Rainfall, Atmospheric, Temperature, Composite, Climate Indices	POAMA	Australia
[67]	ELM	Stream Flow	Monthly	Rainfall, Climate Indices	ANN	Australia

Adaptive Empirical Mode Decomposition-ANN (AEEMD-ANN) [41] and Ensemble Empirical Mode Decomposition-ANN (EEMD-ANN) [46] are among hybrid models developed for that purpose. AEEMD-ANN has proven its superiority in forecasting the runoff in flood season, but not as good as ANN, SVM, Seasonal First-Order Autoregressive (SAR) and ANFIS in the dry season. EEMD-ANN has been reported to enhanced forecasting accuracy better than ANN alone in annual runoff forecasting [46].

In forecasting annual streamflow, EMD, EEMD and Seasonal-Trend Decomposition Using Loess (STL) has been integrated with ANN to provide a model without any basis function [59]. By incorporating "seasonality" instances in the model, it can provide a conducive long-term streamflow forecasting. The hybridization of machine learning model with the decomposition method has led to input optimization that affected how the model behave.

To have a robust long-term machine learning model, it is proposed that the model must be self-adaptive. Self-adaptive model such as Self-Adaptive-Extreme Learning Machine (SaE-ELM) [70] has demonstrate that it can be efficiently applied to produce accurate and reliable monthly water level forecast benefiting from the differential evolution characteristics of robustness, simplicity, and high speed.

Other hybrid machine learning model also been developed for long-term streamflow forecasting such as Adaptive Neuro-Fuzzy Inference System-Fire Fly Algorithm (ANFIS-FFA) [62], Wavelet-Linear Genetic Programming (WLGP) [64], and Bayesian ANN with GR4J (GR4J-ANN) [65]. ANFIS-FFA has been reported to outperform the traditional ANFIS with minimal input but better forecasting performance. This is due to the robustness of the FFA that contribute to the membership function parameters optimization in each input combination [62]. WLGP is a hybrid model that include discrete wavelet transform and linear genetic programming to forecast monthly streamflow. The use of WLGP with multi-resolution time series sub-signals as inputs, has provide better forecast accuracy than single model such as Linear Genetic Programming (LGP), Wavelet-ANN (WANN), ANN and Multi Linear Regression MLR [64].

The use of more conventional model GR4J with ANN [65] has indicated that performance of this hybrid model surpassed the performance of the conventional model GR4J alone in terms of median forecast and forecast distribution. However, this model has the limitation in which two different types of models must be developed for each catchment that can resulting more time and expertise needed. Although hybrid models have given significant effect to the performance of long-term streamflow forecasting, but it may not be suitable to develop for certain region.

Higher quality flow prediction has been reported to be achieved by the hybridization of fuzzy neural network and least squared method (Fuzzy MLP) when compared to the traditional multilayer perceptron [78]. Although this hybrid methods provide less forecast error, but some instances obtained higher value of standard deviation that need to be researched further.

Another hybrid model developed for runoff forecast namely fuzzy neural network–Markov (NFNN-MKV) [43]. This model has able to enhance the mid to long-term runoff forecast for a reservoir system by benefiting the ideal point fuzzy neural network and the Markov forecasting model that able to solve the stationary or volatile strong random process problem [43]. Genetic Algorithm (GA) is an optimization method that based on natural selection. Hybrid methods such as Genetic Algorithm-Support Vector Regression (GA-SVR) [49] has shown great performance in monthly runoff forecasting both in wet and dry period with the influence of the predictor's selection. The use of runoff data together with rainfall and temperature has shown a great impact to the forecasting results.

The potential of genetic algorithm also has been explored by integrating the optimization technique with ANN [22].Two models are developed namely GA Optimized For Artificial Neural Network (GAANN) and Back Propagation Algorithm Optimized for ANN (BPANN). These models are used to forecast Regional Flood Frequency Analysis (RFFA). Although the use of non-linear models is uncommon for RFFA but these two models have proven that they can produce acceptable forecasting result with similar performance.

Hybrid models have proven their capabilities not only in flow and runoff forecasting but also rainfall forecasting. In southeast Australia, Adaptive Network-Based Fuzzy Inference System (ANFIS) has been developed to forecast spring rainfall [27]. This forecast model utilizes the climate signals as predictors and compared the result with the conventional model ANN and POAMA. This study has shown that with accurate predictors selection ANFIS is superior to conventional models in forecasting the spring rainfall. In forecasting monthly rainfall, ensemble empirical mode decomposition integrate with Support Vector Machine (EEMD-SVR) has proven to provide better forecast accuracy compared to ANN, ARIMA and SVR [55]. The study has indicated that decomposition technique by EEMD has provide an efficient technique for analyzing the non-linear and non-stationary hydrologic data.

Although hybrid model has proven its potential to provide a better long-term flood forecast compared to single model, but a study reported the opposite results. A study using hybrid machine learning models by [66] indicates that single-type model ANN and ARMA have outperformed six hybrid models including the wavelet based and Empirical Mode Decomposition based models for monthly streamflow forecasting at Cuntan and Yichang stations. This is due to the use of extension series that giving various performance of the hybrid model.

The hybrid models for long-term flood forecasting are summarized in Table 3.

4. COMPARATIVE ASSESSMENT OF MACHINE LEARNING MODELS FOR LONG-TERM FLOOD FORECASTING

4.1 Type of Parameters

The application of long-term flood forecasting model is derived from the selection of appropriate parameters or flood variables. Historical data from various resources are widely used depending on the forecasted location. There are several parameters that are frequently used by researchers including rainfall, streamflow, climate indices, climate signals, runoff, discharge, and flow. Most of this historical data are gathered from the station itself or from forecast databases and websites such as British Columbia River Forecast Centre (BCRFC) [71], National Ocean and Atmospheric Administration (NOAA) [71], Australian BOM's Climate Data Online [52][53][53], Royal Netherlands Meteorological Institute Climate Explorer [52][53][56],Central Water Commission, Indian Metrological Department's [48], and Department of Irrigation and Drainage Malaysia [69][61][70][62].

Figure 4 indicates parameters used from the primary studies. Researchers may use combination of parameters thus resulting more count for particular parameters. Although in some cases, combination of parameters giving significant impact to the forecasted value but using single flood variable might as well giving

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an acceptable result. Some studies have proven that by introducing multiple input to their studies will produce better model performance [53][44][62]. There is a study reported that by using rainfall data, the accuracy of the model is enhanced [40].

The historical datasets in term of daily, weekly, monthly, or annually used in the primary studies to construct and evaluate the model are ranging from the period of 8 to 145 years. These datasets mostly are divided into training and testing, but some researchers include the validation phase in between.

4.2 Pre-Processing Methods

The use of historical data for the purpose of long-term flood forecasting can affect how the models behave. Original data can be scarce, imperfect, noise, or imbalance, thus it is not appropriate to be used solely for the forecast [69][36][79][80]. The performance of the forecasting model can be enhanced through pre-processing[81][82]. The selection of input is very important as it contribute to the precision and accuracy of the forecast model [33][41].

Table 3: Machine learning for long-term flood forecasting using hybrid models

Reference	Method Proposed	Forecasting Type	Lead Time	Variables	Comparison Method	Region
[39]	WA-ELM	River Flow	Monthly	River Flow	ELM	Iraq
[40]	DWT-RBFNN, QP-DWT-RBFNN	Stream Flow	Monthly	Discharge Rainfall	Q-RBFNN QP-RBFNN	China
[41]	AEEMD-ANN	Stream Flow	Monthly	Runoff	SVM, ANFIS, ANN, SAR	China
[22]	GAANN	Flood Quantiles	Quantiles	Stream Flow, Climatic	BPANN	Australia
[59]	STL-ANN, EEMD-ANN, EMD-ANN	Stream Flow	10 days, Monthly	Stream Flow	Compare each of the proposed method	China
[54]	ANFIS	Rainfall	Seasonal	Rainfall, Climate Signals	ANN, POAMA, Climatology Forecast	Australia
[44]	DWT-FFBP- Q, DWT-FFPB-QP, DWT-RBFNN-Q, DWT- RBFNN- QP	Stream Flow	Monthly	Rainfall, Runoff	FFBP-Q, FFBP-QP, RBFNN-Q, RBFNN-QP	China
[78]	Fuzzy MLP	Water Flow	Monthly	Flow	MLP	Brazil
[49]	GA-SVR, GMDH HYMOD, GA-ANN	Flow Rate	Monthly	Flow	Compare each of the proposed method	Iran
[33]	EMD-SVR-Q, EMD-SVR-QP, EMD-SVR-QP, DWT-SVR-Q, DWT-SVR-QP, DWT-SVR-QP	Stream Flow	Monthly	Runoff, Rainfall	SVR-Q, SVR-QP	China
[45]	G-ELM, I-ELM, W-ELM, W-NN	Runoff	Monthly	Rainfall Runoff	Compare each of the proposed method	Iran

Reference	Method Proposed	Forecasting Type	Lead Time	Variables	Comparison Method	Region
[70]	SaE-ELM	Water Level	Monthly	Water level	ELM	Malaysia
[62]	ANFIS-FFA	Stream Flow	Monthly	Stream Flow	ANFIS	Malaysia
[64]	WLGP	Stream Flow	Monthly	Stream Flow	LGP, ANN, WANN, MLR	Iran
[64][71]	GR4J-ANN	Stream Flow	Monthly	Rainfall, Daily Flow, PET data, Rainfall Forecast, Groundwater Level, Soil Moisture Index	GR4J ANN	Australia
[55]	EEMD-SVR	Rainfall	Monthly	Rainfall	ANN, ARIMA, SVR	China
[46]	EEMD-ANN	Runoff	Annually	Runoff	ANN	China
[66]	WA-ANN, WA-ARMA, EMD-ANN, EMD-ARMA, SSA-ANN, SSA-ARMA	Stream Flow	Monthly	Stream Flow	Compare each of the proposed method	China
[43]	NFNN-MKV	Inflow	Annually Monthly	Rainfall, Inflow, Discharge	MKV, FNN, SVR WNN	China
[60]	GEP-NGRGO	Flow	Monthly	Flow	ARIMA	Iraq

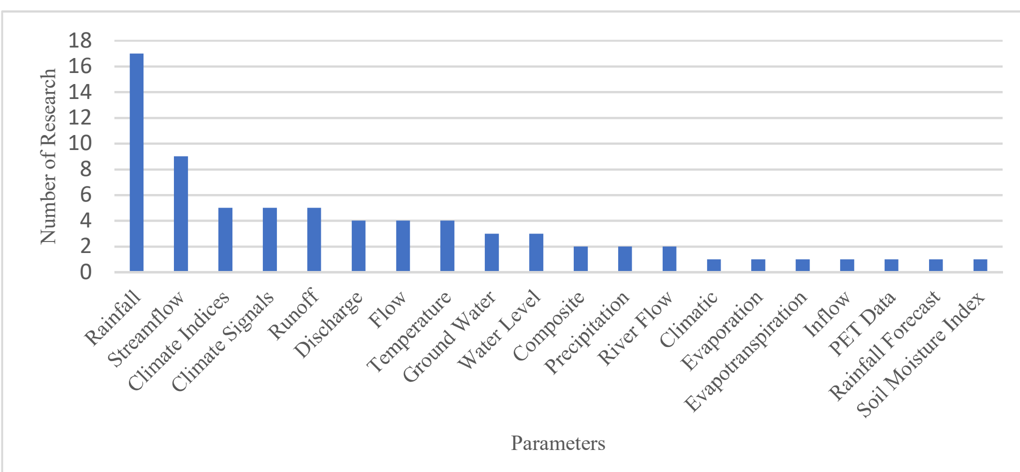

Figure 4: Parameters used in the machine learning model for long-term flood forecasting

Figure 5 summarizes the pre-processing methods used in the primary studies. Wavelet Transform (WT) is the most method apply by the researchers followed by Ensemble Empirical Wavelet Decomposition (EEMD), Cross Correlation Function (CCF), and Genetic Algorithm (GA). Other technique includes Autocorrelation function (ACF) and Partial Autocorrelation Function (PACF), Empirical Wavelet Decomposition (EMD), Aggregation, Differential Evolution (DE), Singular Spectrum Analysis (SSA), Maximum Relevance-Minimum Redundancy (MRMR), and Seasonal-Trend Decomposition Using Loess (STL).

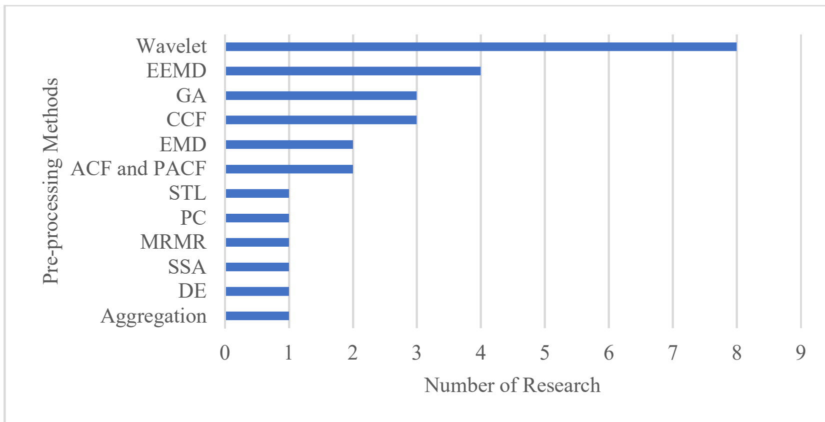

Figure 5: Pre-processing methods

The use of wavelet decomposition such as Discrete Wavelet Transform (DWT) decomposed time series data into shifted and scaled version of a wavelet, a mother wavelet [44]. It is a useful method that able to analyse time-series variation that give information on time and frequency domains of signal. DWT is more efficient than calculating wavelet coefficient at each possible scale in the continuous wavelet transform that takes more of process work [64]. Although DWT is a great pre-processing technique, but it is sensitive in the selection of mother wavelet [83][33][66]. The decomposition level and mother wavelet must be predetermined. Wavelet transform is suitable for non-stationary data processing, but data must be linear [41].

The decomposition technique of DWT has been proven to improved forecast performance [40][44][33][64] but in some cases the decomposition of such time series data did not giving any significant difference in term of the forecast accuracy. This is because wavelet analysis is based on the convolution of the signal with the filter, that can lead to border distortions when performed on finite-length signals [66]. The drawback of DWT is it has a problem called shift variance behaviour in which it varies the energy of DWT result depending on only one sample delay of an original signal. It is said that down sampling causes the problem [84].

Empirical Model Decomposition (EMD) [85] decomposes nonlinear signal into Intrinsic Mode Functions (IMFs) and one residual component. Unlike DWT, EMD can decompose time series data which is non-stationary and non-linear [59]. EMD has the advantages over the DWT as EMD has its full self-adaptiveness and requiring no predetermined basis function [41]. EMD has the drawbacks of having the frequent occurrence of mode mixing [55]. This drawback has motivated researcher to propose an ensemble empirical mode decomposition (EEMD)[86]. EEMD decomposing technique add finite noise to the signal that can address the mode mixing problem of EMD [55][46].

The use of EEMD has effectively improve the forecasting model. It also found that the use of different length time series data in EEMD could produce various performance of the model in which the decomposition and model must be updated whenever new information is added [41]. The self-adaptability of EMD and EEMD can be the point of difficulty when applying this method as different time series will produce different number of IMFs. This will form disagreement of the input data during training and forecasting phase [59]. Although EEMD seems to stabilize the obtained decomposition, but it increases the computational cost [87].

Cross Correlation Function (CCF) function is used to select important variables for the model [60]. It is measuring the linearity of similarity between two signals. CCF is used in studies [73] to determine time lag and input variables for the model. Genetic Algorithm (GA) is an optimization method based on the principles of genetics and natural selection [49]. It relies on operators inspired by the biological process such as mutation, crossover, and selection. GA has been used to optimize input for the model [33][65] and finding optimal kernel function for the model parameters [49]. Differential Evolution (DE) has been introduced to address the drawback of GA in lack of local search [88]. It can provide solution for a complex problem with the least error. Although DE has overcome GA drawback, but it can be too stochastic or too greedy.

Other methods used in pre-processing is Auto-correlation function (ACF) and the Partial auto-correlation function (PACF) to find the most correlated inputs to perform the model effectively [61][75]. Aggregation is used to transform original data series into monthly data series [72]. Singular Spectrum Analysis (SSA) has been used and prove to eliminate the boundary effect problem occurred when using DWT and EMD methods [66]. Maximum Relevance-Minimum Redundancy (MRMR) method is employed to select the most effective forecasting features from the climate signals [71]. Seasonal-Trend Decomposition Using Loess (STL) is used to splits time series data into trend and seasonal. Loess smoothing then apply to determine and estimate the seasonal component and trend component [59]. STL helps in improving the accuracy of the estimated components.

The application of pre-processing technique playing an important role as it provides optimization to the selection of the input parameters to the model. The studies indicate that the behaviour of the model is improving when pre-processing is done resulting better forecast accuracy. The pre-processing techniques also can be difficult to perform such as EMD, EEMD and STL due to their self-adaptability. It is revealed that some pre-processing techniques is superior to the others. In their study DWT has outperformed EMD in term of the model performance [33].

4.3 Performance Measurements

In the ideal situation, the forecasting model will be evaluated using performance measurements. Evaluation might be used to generalize the result and comparing the forecast model to a reasonable alternative [89]. The evaluation of forecast model can be done during the training and testing stage. From the primary studies, evaluation is done by examining the outputs. The primary concern of the evaluation is accuracy and performance of the model. Figure 6 indicates the performance measurements used by the researchers. The models might be assessed by single evaluation measurement or combination of multiple measurements.

It is revealed that the most performance measurement used by the researchers is Root Mean Square Errors (RMSE), followed by Mean Absolute Error (MAE), Nash-Sutcliffe Efficiency (NSE), Correlation Coefficient (R), Coefficient of Determination (R2) and Mean Absolute Percent Error (MAPE). MAE is a simple measure of forecast accuracy. It calculates the absolute error in which the absolute value of the difference between the actual and forecasted value. It provides the researcher information on how great the error that can be accept from the forecast on average. MAE can be a problem when the relative size of error is not obvious where the different between small error and big error cannot be tell.

MAPE overcome this problem by providing the mean absolute error in the term of percentage. MAPE allowed the researcher to make comparison between different series and scale of data. MAE and MAPE focusing on the mean error but sometimes error can be big but infrequent. This kind of rare errors can be adjusted by using RMSE. RMSE squaring the errors before the mean calculation been done. The square root of the mean than calculated to measure the error in which will giving more weight to infrequent large error.

Correlation Coefficient (R) is used to measure the greatness of relationship between data or variables. The strength of the relationship denotes by the value of the correlation coefficient, in which the larger value giving the stronger relationship.

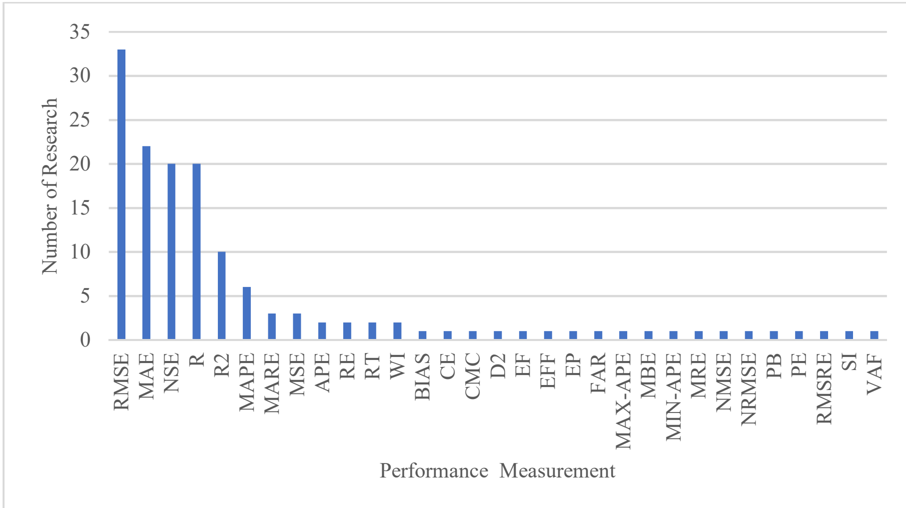

Figure 6: Performance Measurements

Coefficient of Determination (R_2) in the other hand is literally the square value of the correlation. It denotes the percentage of the response variable variation that is explained by a model. Although correlation coefficient and coefficient of determination would provide goodness of fit index, in theory, it only applicable to linear models. Furthermore, the computed value can be poor estimated due to model bias [89].

To overcome the limitation of correlation coefficient, NSE is proposed to be used as an alternative to calculate the efficiency of the hydrological model. It describes the accuracy of the forecast model as long as it can be compared to the observed data. The advantages of NSE are it can be applied to various type of model including the nonlinear model. Although NSE is a great alternative for assessing the goodness of fit of a model, it is difficult to interpret as the sampling distribution is not presented resulting only subjective interpretation can be made towards the sample values [89]. The evaluation measurement in general is used to prove how the models being developed can accurately predicted the forecast value.

5. CONCLUSION

Research studies over the recent years on the use of machine learning in long-term flood forecasting has shown a great interest among the researchers. Machine learning can analyse the historical data without knowing the underlying process and has the self-adaptive capability in which it iteratively adapts when exposed to new data. The non-linearity and non-stationary of hydrological data is a challenging factor in providing an accurate forecast. There is various type of hydrological data used in flood forecasting including rainfall, streamflow, runoff, and climate signals. Rainfall data is widely used by the primary studies and the use of it as input has contributed to the accurate forecasting.

To provide meaningful input to the long-term flood forecasting model, optimization of the nonlinear hydrological time series data is crucial. Addressing this issue, many primary studies has implemented optimization method in pre-processing phase. Optimization method helps the features of the data interpreted by the models. Methods such as Wavelet Transform (WT) and Empirical Ensemble Mode Decomposition (EEMD) are widely used in which signals are decomposed into specific modes and self-adapting.

Long-term flood forecasting model can be developed using single or through hybridization. Models which are hybrid with optimization techniques or other conventional model has been proved to outperformed single model in most of the studies. Developed machine learning models must be evaluated to measure the performance and accuracy. Various evaluation measurement can be used such as RMSE, MAE and NSE.

This study presents the systematic literature review of machine learning model in long-term flood forecasting. The objective is to provide insights of machine learning models in long-term flood forecasting by gathering and analysing the knowledge from the literature to facilitate researchers in future studies in the same domain. This study collected data from primary studies in various repositories. Forty (40) primary papers are identified which is published either in journals, conferences, or chapters. All of them are passed the quality assessment. Data are extracted and analyse to provide information regarding of machine learning model in long-term flood forecasting.

From this study, it is found that although there are many literatures proving the performances of various machine learning models but there is no certain conclusion been made as which model is the best in long-term flood forecasting. Among the factors that influenced the performances are, the input type, pre-processing methods, and location.

For the machine learning models to perform well with minimal error, it is proposed that the development stages adopted three strategies. The first strategy involved optimizing the original input with optimization method such as wavelet decomposition that can analyse the data and extract pertinent information to be used as input for the model. Second strategy is to optimize existing machine learning algorithm by tuning the hyperparameters or modifying the algorithm with additional optimizer. The last strategy is to hybrid the machine learning models. Hybridization can be done between 2 or several machine learning models through integration or ensemble. These strategies can be implemented in the development of machine learning model for long-term flood forecasting either single or in collective manner.

The in-depth review of this study can be critical resources for researcher and provide guidance in determining a suitable machine learning models to be developed for the purpose of forecasting. Nevertheless, this study does have its limitations. First limitation is this study only used six of the widely literature repositories that available. Secondly, Search strategy is performed with limited keywords to get only related literatures. Keyword search is not used in Google Scholar to avoid all papers being listed with those keywords. Thirdly, paper might be skipped during the search strategy although their domain is related. This is due their study does not use the term at all. This study can be a valuable resource for researchers in equipping them with the insights and detail of the use of machine learning in long-term flood forecasting.

To help researchers gaining more insights and knowledge of the machine learning models in long-term flood forecasting, it is suggested that future work involve conducting thorough review on the hybridization of the models. This is due to the potential of hybridization techniques that harness the advantages of several algorithm that can help in improving the model performance.

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